

# Do climate variations explain international migration?

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# Motivation

- Nexus climate change and migration addressed since the early 1990s by political scientists, environmentalists and demographers
- Substantial media coverage but limited academic research
- Mainly case studies for specific regions/countries and time episodes (World Bank, 2010)
- The number of empirical studies quantifying this impact is limited

# Motivation (cont)

- Natural disasters and extreme events as drivers: Marchiori, Maystadt and Schumacher, 2011; Lilleor and Van den Broeck, 2011; Beine and Parsons, 2015; Groeschl and Steinwachs, 2016
- I focus on **permanent migration due to gradual climate change** (Backhaus et al, 2015; Cai et al, 2016; Cattaneo and Peri, 2016)
- Investigate further the differential effect found by Cattaneo and Peri (2016) for different country groups → using Backhaus et al dataset
- Target variables: Average temperature and precipitation

# Related Literature

*Early multi-country studies on the link migration-climate change:*

- *Barrios (2006) on internal migration:* rainfall shocks induce internal migration in SSA but not in other developing countries,
- *Marchiori et al. (2011) on international migration:* 43 SSA countries, climate variations increase the incentives to migrate internationally via changes in the wage ratio, but urbanisation mitigates the effect on international migration

*GDP growth and climate change:*

- Dell et al. (2008) use **within-country year-to-year fluctuations in the climatic variables** in order to partially overcome omitted variable bias due to other unobservable country-specific determinants of GDP

# Related Literature (cont)

- Effect of average temperature and rainfall on emigration →
  - Backhaus et al., 2015: GM, *yearly* inflows
  - Cai et al., 2016: GM, *yearly* emigration rate
  - Cattaneo and Peri, 2016 : Country-decade emig. Rates
- Deviations of rainfall and temperature from “normal” levels, natural disasters →
  - Beine and Parsons, 2015: GM, decade, inflows
  - Coniglio and Pesce, 2016 : GM, *yearly*

# Related Literature (cont)

**Backhaus et al., 2015:** Average temperature positively correlated with bilateral migration, mainly *for agricultural-dependent countries*

**Cai et al.:** Each 1 °C increase in temperature implies a 5% increase in out migration from the top 25% *agricultural countries* (significant at the 1% level)

**Cattaneo and Peri, 2016:** Climatic warming associated with significantly higher emigration rates in *middle-income countries and significantly lower rates in poor countries*

**Beine and Parsons, 2015:** No evidence of direct impacts of climate anomalies on international migration but only an indirect effect through wage differentials

**Coniglio and Pesce, 2016:** An increase in rainfall variability (also in anomalies) is associated with an increase in average bilateral migration

Study	Countries	Period	Method	Migration type and measure	Climate variables	Main Finding
<b>Barrios et al (2006)</b>	78 countries	1960-1990	Cross-country panel data with country and time FE	Internal, Urbanization as a proxy	Rainfall level normalized by the mean	Rainfall shocks induce migration in SSA only
<b>Marchiori et al (2012)</b>	43 SSA countries	1960-2000,	Cross-country panel data with country and time-region FE	International, Net migration rate	Precipitation and temperature anomalies	Positive (negative) effect of rainfall (temperature) anomalies via wage ratio
<b>Backhaus et al (2015)</b>	142 sending countries to 19 OECD destinations	1995-2006, yearly basis	Gravity model with country-pair and time FE, estimation in first differences	International, Bilateral migration inflows	Population-weighted Average temperature and precipitation	Average temperature is positively correlated with bilateral migration, mainly for agricultural-dependent countries
<b>Beine and Parsons (2015)</b>	226 origin and destination countries	1960-2000, ten year intervals (5 waves)	Gravity model with origin and destination-time FE (PPML)	International, bilateral migration rate	natural disasters and average deviations of decadal average temperature and rainfall and anomalies	no evidence of direct impacts of climate anomalies on international migration but only an indirect effect through wage differentials
<b>Coniglio and Pesce (2015)</b>	128 origin and 29 OECD destinations (Listed in online Appendix)	1990-2001, yearly basis	Gravity model with origin and destination-time FE (PPML)	International, Bilateral migration inflows	Rainfall and temperature surplus and deficit, index of excess rainfall variability	an increase in rainfall variability (also in anomalies) is associated with an increase in average bilateral migration
<b>Cai et al (2016)</b>	163 sending countries to 42 destinations	1980-2010, yearly basis	Gravity model with country-pair and origin and destination linear trends	International, bilateral migration rate	Population-weighted Average temperature and precipitation	Each 1 °C increase in temperature implies a 5% increase in out migration from the top 25% agricultural countries (significant at the 1% level)
<b>Cattaneo and Peri (2016)</b>	115 sending and receiving countries (30 poor and 85 middle-income) (Data in online Appendix)	1960-2000, ten year intervals	Cross-country panel data with country and time-region FE	International, Net emigration flows (diff between stocks in two consecutive census) from Ozden et al. (2011)	Population-weighted Average temperature and precipitation from Dell et al. (2012)	climatic warming associated with significantly higher emigration rates in middle-income countries and significantly lower rates in poor countries

# Modelling framework

- The neoclassical approach to migration: a rational individual that takes his decision to migrate on purely economic grounds and acts independently of other social entities: Borjas (2005)
- In a simple 2-period model (Cattaneo and Peri, 2016), the decision to migrate for individual  $i$  *implies a comparison* between the net income when migrating and staying. Thus,

*(wage destination-cost of migrate) > wage origin* → Mig.



# Predictions

- P1: An increase in average temperature → Increases the emigration rate in middle-income countries
- P2: An increase in average temperature → Decreases the emigration rate in poor countries, because their wages are not high enough to cover the monetary cost of migration
- Considering a sending country (s) that is middle or low income (P), the derived empirical model is,

$$\ln \left( \frac{Mig_s}{Pop_s} \right) = \alpha + \gamma \ln T_s + \gamma_P \ln T_s D(s \in P) + \beta C_s \quad (1)$$

# Empirical strategy

- We use the same approach as in Cattaneo and Peri (2016) and estimate equation (1) using Backhaus et al. dataset using only climatic variables and a battery of fixed effects:
- Adding year-quartile income distribution interaction dummy variables
- Time-region dummy variables

# Empirical strategy (cont)

- We also use the grouped fixed-effects (GFE) approach recently proposed by Bonhomme and Manresa (2015)
- Introduces time-varying grouped patterns of heterogeneity in linear panel data models that are common within groups of countries.
- Both the group-specific time patterns and the group membership are estimated from the data.

$$\ln \text{Mig}_{it} = \mathbf{x}'_{it} \boldsymbol{\beta} + \gamma_{g,t} + u_{it} \quad (2)$$

# Empirical strategy

- The GFE in model (2) is the outcome of the minimization of the following expression:

$$(\hat{\beta}, \hat{\gamma}, \hat{\alpha}) = \underset{(\beta, \gamma, \alpha) \in \Theta \times A^{GT} \times \Gamma_G}{\operatorname{argmin}} \sum_i^N \sum_t^T (\ln \operatorname{Mig}_{it} - x'_{it} \beta - \gamma_{g_{i,t}})^2 \quad (3)$$

where the minimum is taken over all possible groupings  $\alpha = \{g_1, \dots, g_n\}$  of the  $N$  units into groups  $G$ , parameters  $\beta$  and group-specific time effects  $\gamma$

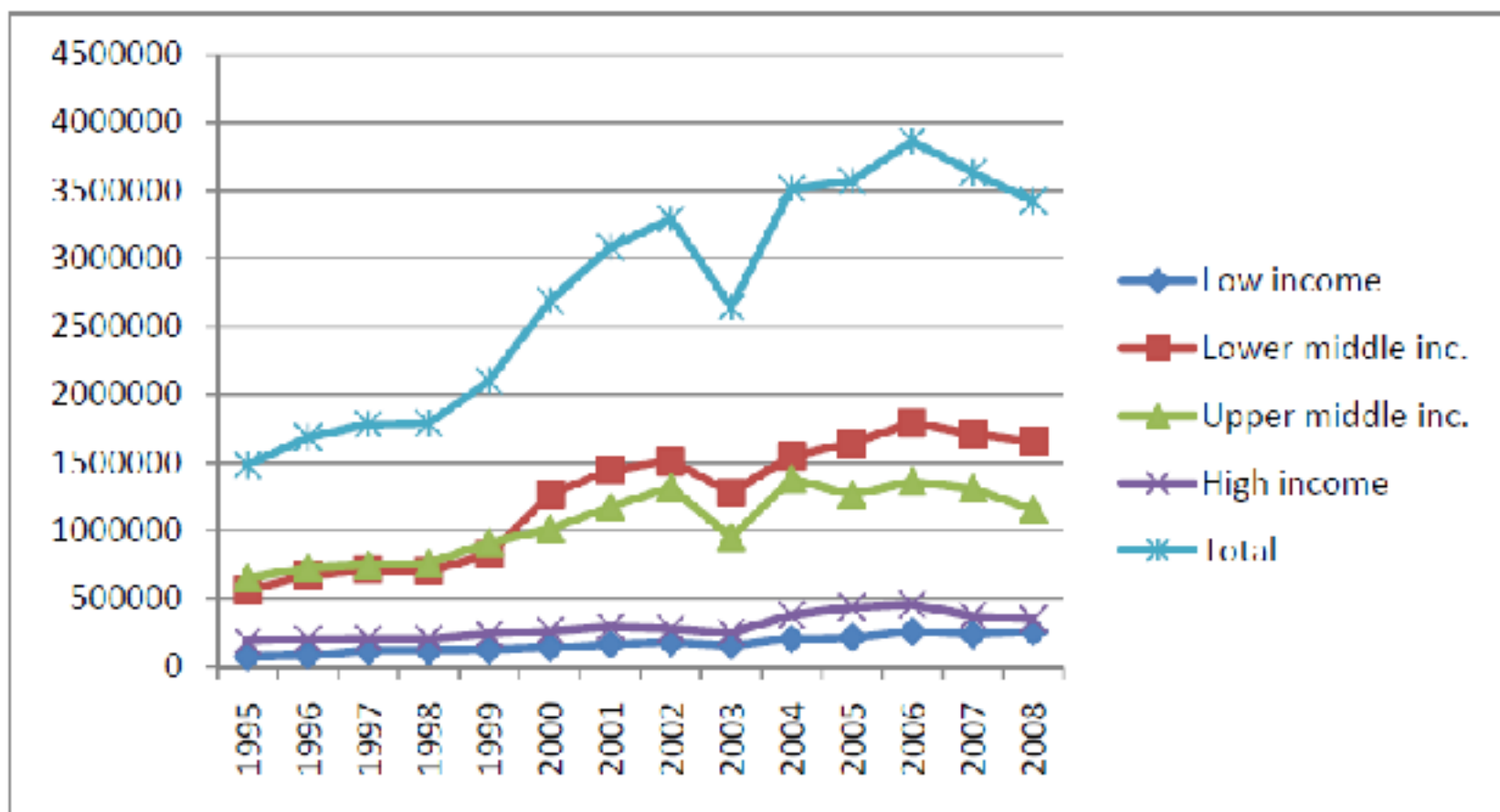
# Data and Variables

- Dataset 1: Backhaus et al (2015):
  - Migration flows and stocks in destination countries are mainly from the OECD's International Migration Database (IMD) from 1995 to 2008
  - Average temperature and average precipitation both are from Dell et al (2008) → Geospatial software used to aggregate both variables to the country-year level
  - Sample: 1995-2006, 19 destinations and 127(161) origins
- Dataset 2: Cattaneo and Peri (2016)
  - Sample: Decade data 1960-2000, 115 non-OECD countries, emig. Rates (and urbanization)

# Data and Variables

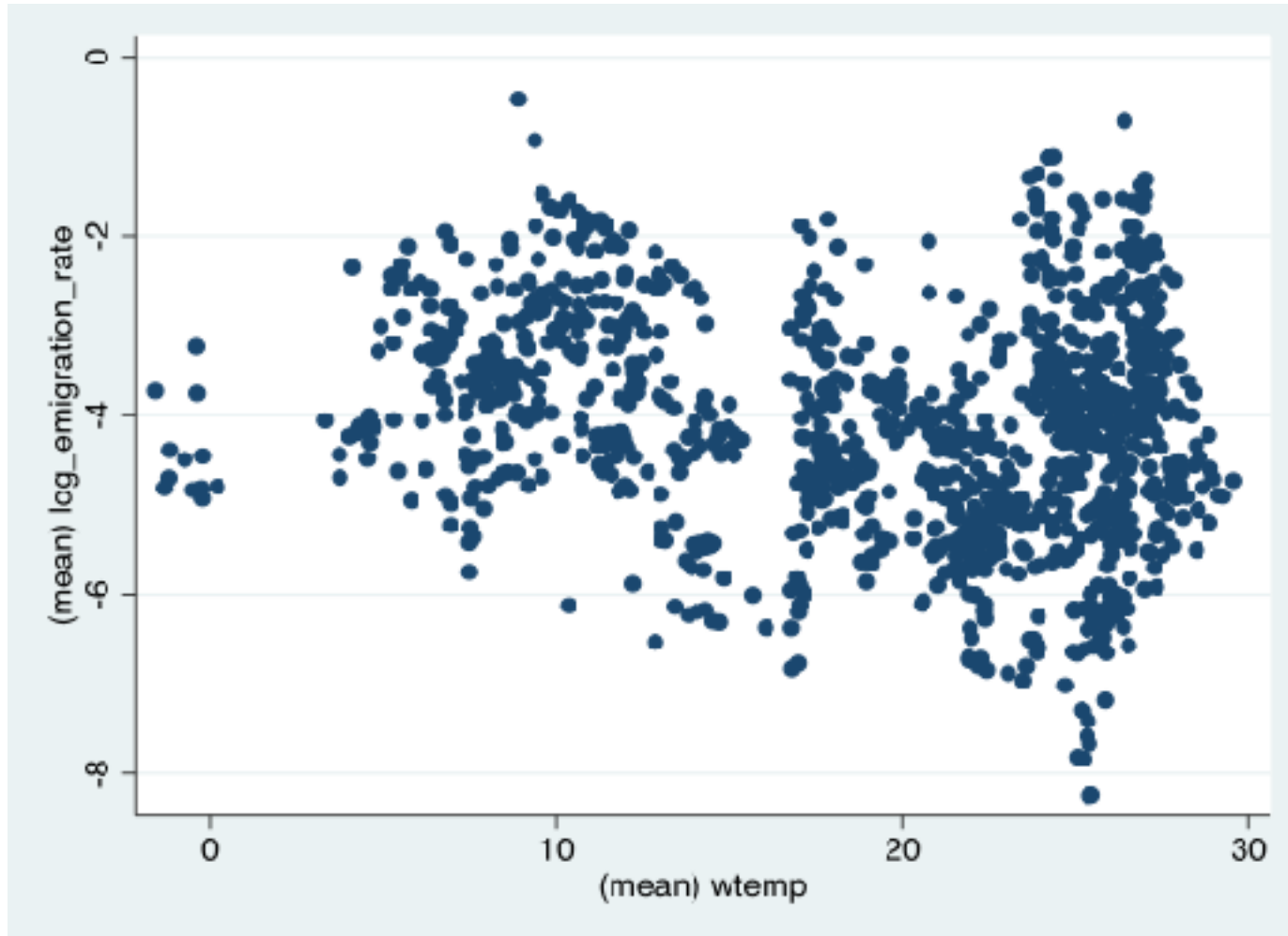
## **Migration (Backhaus et al):**

- In total, about 38.5 m. people emigrated from their home countries and moved to the destination countries during the observation period: 1995-2008
  - 44.94% originate from lower-middle-income countries
  - 38.16% from upper-middle-income
- The high- and low-income countries (10.7 % and 6.11%) exhibit the smallest emigration flows both in absolute and relative terms.
- The second case might be an indication of poverty constraint on migration



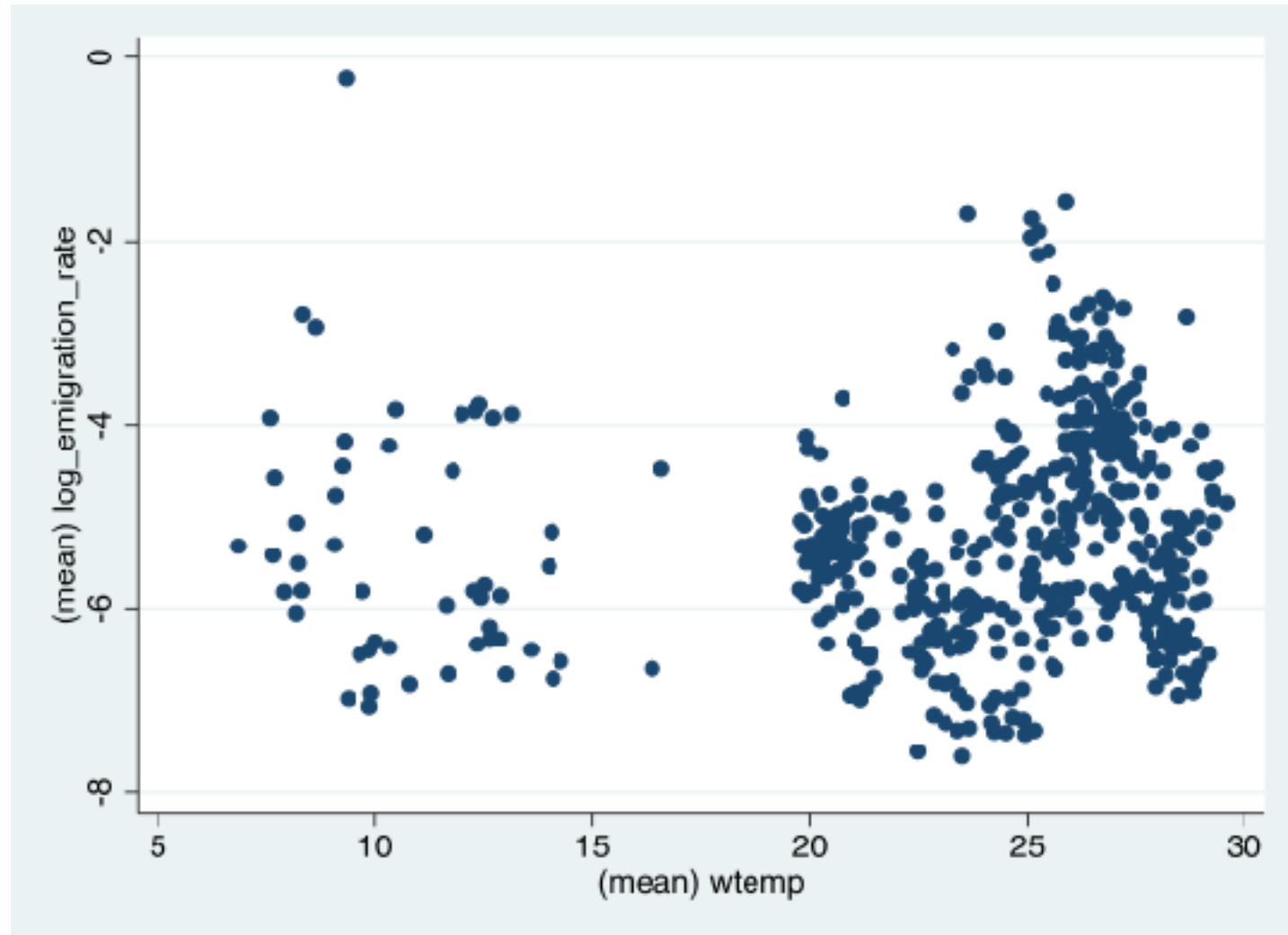
**Figure 1: Emigration by source country income classification over time**

# Scatter plot MIC





# Scatter plot LIC



# Summary statistics (dataset 1)

Variable	Obs	Mean	Std. Dev.	
emigration rate	1,704	0.137	0.247	
log_emigrate	1,693	-4.441	1.301	Mean Emigration rate
wtemp	1,704	20.643	6.888	Poor=0.04
wpre	1,704	10.910	7.415	MIC=0.17
gdpcap_ 1000	1,605	5.580	7.922	
log_pop	1,704	15.814	1.689	
demographic presure	1,704	59.478	6.487	
stability	1,134	-0.369	0.925	
sfi	1,613	11.777	5.942	
unemployment	778	10.023	6.454	
max_temp	1,704	21.294	6.742	
min_temp	1,704	19.940	7.088	
Share agricultural land	1,704	41.107	22.445	
steady_wtemp_change	1,278	0.128	0.335	
steady_wpre_change	1,278	0.095	0.293	
inflows	1,704	1370.405	2640.830	
log_inflows	1,693	4.474	1.614	

# Summary statistics (dataset 2)

**Table 1**  
Summary statistics.

Countries included in the sample	Non-OECD sample middle-income countries			Non-OECD sample poor countries		
	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.
Emigration rate (emigration flows/population)	338	0.042	0.034	120	0.018	0.020
Temperature, °C (pop weight)	338	22.118	4.925	120	23.499	4.172
Precipitation, 100s mm/year (pop weight)	338	13.406	8.818	120	11.407	5.157
Temperature, °C (area weight)	330	22.251	5.054	120	23.894	3.968
Precipitation, 100s mm/year (area weight)	330	13.255	9.175	120	10.894	5.742
Share of urban population	420	0.422	0.222	145	0.194	0.112
Emigration rate (to non-OECD destinations)	338	0.014	0.034	120	0.014	0.018
Emigration rate (to OECD destinations)	338	0.028	0.073	120	0.004	0.007
Emigration rate (to close destinations)	289	0.009	0.037	104	0.010	0.018
Emigration rate (to distant destinations)	338	0.033	0.055	120	0.009	0.011
Agriculture, value added (% of GDP) (WDI source)	242	16.298	11.147	83	34.787	11.992

Note: The first three columns of the table show the summary statistics including as country of origin of immigrants non-OECD countries, excluding those in the bottom quartile of the GDP per capita distribution. The remaining three columns show the summary statistics for the sample of non-OECD countries in the bottom quartile of the GDP per capita distribution. The sample is supposed to include countries of the world that are "Poor" or "Middle-Income".

Source: Cattaneo and Peri (2016)

## Main Results

Replication of Cattaneo  
and Peri,C&P (2016) with  
Backhaus et al (2015) data

Dep. Variable: <b>ln_emig rate</b>	(1) <b>FE</b>	(2) <b>FE</b>	(3) <b>FE</b>	<b>C&amp;P (2016)</b>
<b>Exp. Variables:</b>	<b>no_logs</b>	<b>logs</b>	<b>logs</b>	<b>logs</b>
wtemp_initxtilegdp1	-0.162 [0.105]	<b>-4.527**</b> [2.154]	<b>-4.842**</b> [2.430]	<b>-16.476***</b> (6.250)
wtemp_initxtilegdp2	-0.0247 [0.0924]	0.828 [1.368]	1.564 [1.198]	7.474 (6.824)
wtemp_initxtilegdp3	<b>0.124*</b> [0.0700]	<b>1.947***</b> [0.734]	<b>2.086***</b> [0.751]	<b>8.614*</b> (5.143)
wtemp_initxtilegdp4	0.0633 [0.0639]	<b>1.595***</b> [0.435]	<b>1.980***</b> [0.527]	<b>2.840**</b> (1.391)
wpre_initxtilegdp1	-0.0157 [0.0127]	<b>-0.273*</b> [0.156]	<b>-0.335**</b> [0.162]	-1.643 (1.902)
wpre_initxtilegdp2	0.0204 [0.0153]	<b>0.256*</b> [0.142]	<b>0.343**</b> [0.142]	<b>-1.684**</b> (0.658)
wpre_initxtilegdp3	0.0163 [0.0163]	0.0994 [0.137]	0.0474 [0.137]	0.097 (0.404)
wpre_initxtilegdp4	0.00848 [0.0124]	0.032 [0.175]	0.0182 [0.207]	0.434 (0.642)
Country FE	Yes	Yes	Yes	Yes
Year (decade)-quartile FE	Yes	Yes	Yes	Yes
Year3 (decade)-region FE	Yes	Yes	Yes	Yes
Observations	1,522	1,511	1,367	458
R-squared	0.294	0.306	0.335	0.249
Number of cid	127	127	115	115

## Table 2

- Similar results with same 115 countries

## Main Results

Replication of Cattaneo  
and Peri (2016) with  
Backhaus et al (2015) data

### • Table 3

Increase in temp of 1% :  
Increases emig rates by  
almost 2% (4%C&P) in  
MIC

Decreases emig rates by  
almost 5% (16% C&P) in  
LIC

Dep. Variable:	(1)	(2)	(3)	C&P (2016)
In_emig rate	FE	FE	FE	FE
Exp. Variables:	no_logs	logs	logs	Nologs/logs
wtemp	0.0548 [0.0450]			<b>0.267*</b> [0.155]
wtempoor	<b>-0.198*</b> [0.117]			<b>-1.127***</b> [0.336]
wpre	<b>0.0182**</b> [0.00890]			-0.013 [0.024]
wprepoor	<b>-0.0301**</b> [0.0132]			-0.159 [0.116]
Inwtem		1.706*** [0.408]	<b>1.946***</b> [0.425]	<b>3.755**</b> (1.661)
Inwtempoor		-6.540*** [2.459]	<b>-6.799***</b> [2.468]	<b>-19.967***</b> (6.607)
Inwpre		0.0977 [0.0946]	0.105 [0.108]	-0.223 (0.325)
Inwprepoor		-0.433** [0.187]	<b>-0.440**</b> [0.194]	-1.399 (1.912)
FE (as in Table 2)				
Observations	1,522	1,511	1,367	458
R-squared	0.340	0.315	0.334	0.05/0.201
Number of cid	127	127	115	115

Robust standard errors in brackets

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

## Main Results

Replication of Cattaneo  
and Peri (2016) with  
Backhaus et al (2015)  
data

Table 5

- **Only in the second sample:** A non-linearity in temp also captures the changes in the marginal impact on migration

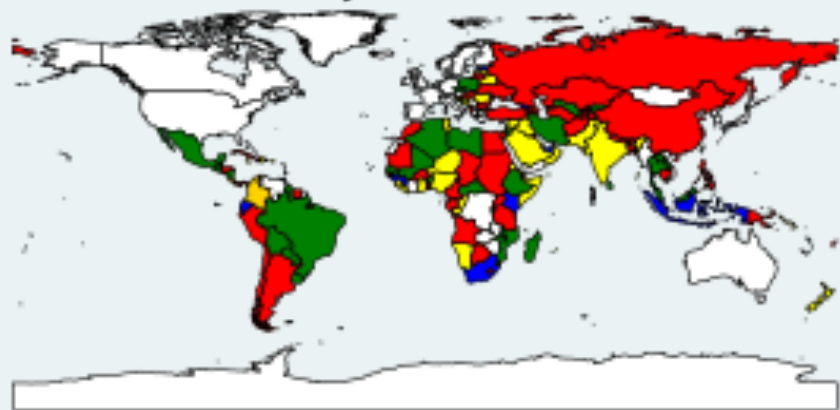
	(1)	(2)	(3)
VARIABLES	FE	FE	FE
		MIC	Poor
Inwtem	7.317***	7.194***	-27.45***
	[1.834]	[2.209]	[8.012]
Inwtem_squared	-1.380***	-1.838***	3.520**
	[0.435]	[0.542]	[1.613]
Inwpre	-0.0392	0.0800	-2.225*
	[0.122]	[0.136]	[1.152]
Inwpre_squared	0.0287	0.0184	0.391
	[0.0273]	[0.0324]	[0.273]
Country FE	yes	yes	yes
Year3-region FE	yes	yes	yes
Observations	1,367	1,072	384
R-squared	0.321	0.034	0.134
Number of cid	115	91	32
Robust standard errors in brackets			
*** p<0.01, ** p<0.05, * p<0.1			

# Preliminary Results GFE

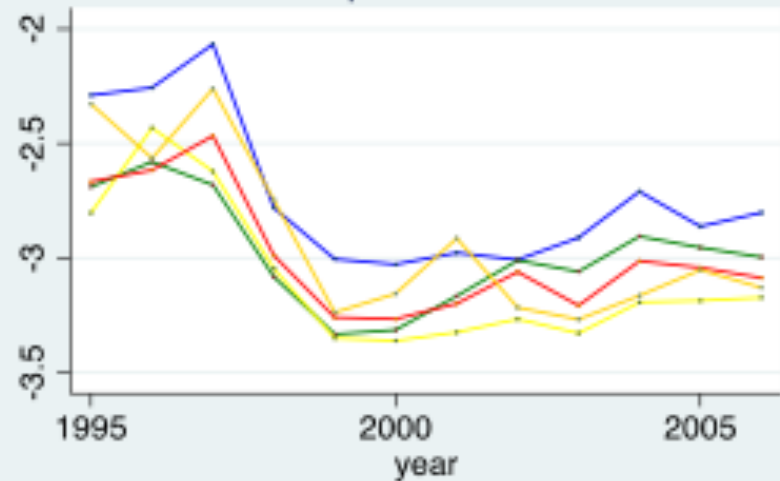
- **Only first sample:**
- Model with non-linearities in weighted-temperature and weighted-precipitation

log_emigration rate	Coef.	Std. Err.
(G=4)	With group FE	
	-0.1477**	
wtemp	*	0.0135
Wtemp_squared	0.0035***	0.0004
wpre	0.0558***	0.0084
	-0.0015**	
Wpre_squared	*	0.0002
log_gdpcap	1.5266***	0.2469
	-0.0668**	
log_gdpcap2	*	0.0149
	-1.7371**	
_lassignmen_2	*	0.2118
Turning points for wtemp=21.61 degrees centigrades	-0.7370**	
_lassignmen_3	*	0.2299
	-2.8100**	
_lassignmen_4	*	0.2402

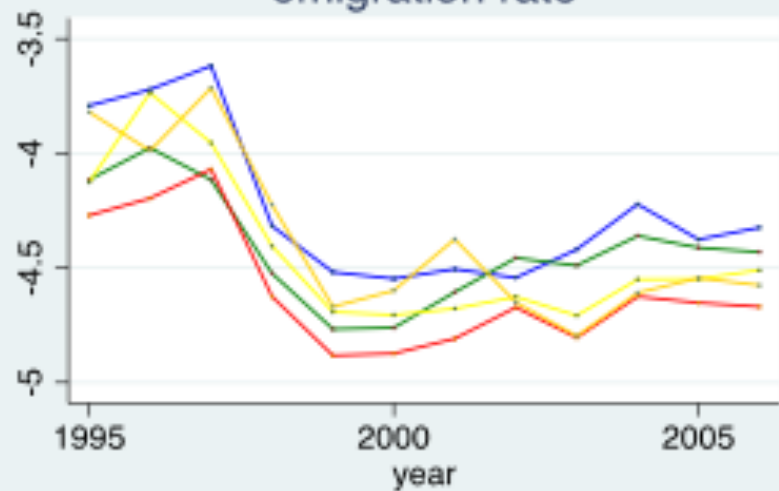
### Country Classification



### Grouped Patterns



### emigration rate





# Other Results GFE (cont)

<b>log_emigration_rate</b>	<b>Coef.</b>	<b>Std. Err.</b>	<b>t</b>	
<b>wtemp</b>	<b>0.224**</b>	<b>0.087</b>	<b>2.56</b>	<ul style="list-style-type: none"><li>• <b>Only first sample:</b></li><li>• Model with interaction term between weighted-temperature and log GDP per capita</li></ul>
wpre	0.056	0.071	0.79	
log_gdpcap	1.144***	0.224	5.1	
<b>wtemp*loggdpcap</b>	<b>-0.032***</b>	<b>0.010</b>	<b>-3.11</b>	
wpre*loggdpcap	-0.003	0.008	-0.36	
_lassignmen_2	0.945	0.261	3.61	
_lassignmen_3	-0.182	0.280	-0.65	
<b>_lassignmen_4</b>	<b>1.544</b>	<b>0.401</b>	<b>3.85</b>	

# Conclusions

- There are incentives but also constraints to migrate
- Increasing temperature in origin increases emigration rates in middle income countries, but decreases emigration rates in low income countries
- Results found using yearly data 1995-2006 in line with results using decade-data 1970-2000
- Lower precipitation increases emigration rate only in LIC the second sample

# Further research

- Examining different groups of countries using bilateral migration data
- Simulations for different countries according to different scenarios (IPCC)
- Optimal number of Groups in GFE when grouping countries endogenously

Thanks for your attention

# Gravity Model applied to dataset 1

- **Main factors that determine migration:**
- Income origin and destination  $\rightarrow +, (-)$
- Unemployment rates or and dest  $\rightarrow +, (-)$
- Travel cost  $\rightarrow (-)$
- Immigr. policies destination, stability origin
- Cultural similarities: colonial rel, trade, (+)
- Others: Inequality, capital market imperf, demography
- Climatic factors

# Empirical strategy

- GM specification that models time-variant multilateral resistance (dest), as suggested in the trade literature

$$\begin{aligned} \ln M_{ijt} = & \alpha_0 + \alpha_1 \ln w_{tem_{it}} + \alpha_2 \ln w_{pre_{it}} + \alpha_3 \ln GDP_{it} + \alpha_5 \text{DemPre}_{it} + \alpha_6 U_{it} \\ & + \alpha_8 \text{TradeGDP}_{it} + \alpha_9 \ln \text{Dist}_{ij} + \alpha_{10} \text{Contig}_{ij} + \alpha_{11} \text{Lang}_{ij} + \alpha_{12} \text{SameCont}_{ij} + \\ & \alpha_{13} \text{Colony}_{ij} + \alpha_{14} \text{EU}_{ijt} + \varphi_t + \omega_{jt} + \mu_{ijt} \end{aligned}$$

# Empirical strategy (cont)

- A second specification adds dynamics as suggested recently (Dunlevy, 1993, Ruysen et al., 2011)

$$\ln M_{ijt} = \alpha_0 + \delta_1 M_{ij,t-1} + \delta_2 MS_{ij,t-1} + \alpha_1 \ln w_{tem,it} + \alpha_2 \ln w_{pre,it} + \alpha_3 \ln GDPH_{it} + \alpha_5 \text{DemPre}_{it} + \alpha_6 U_{it} + \alpha_8 \text{TradeGDP}_{it} + \alpha_9 \ln \text{Dist}_{ij} + \alpha_{10} \text{Contig}_{ij} + \alpha_{11} \text{Lang}_{ij} + \alpha_{12} \text{SameCont}_{ij} + \alpha_{13} \text{Colony}_{ij} + \alpha_{14} \text{EU}_{ijt} + \varphi_t + \omega_{jt} + \mu_{ijt}$$

# Sum Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ln_inflows	17643	4.663284	2.518515	0	12.29601
ln_stocks	12050	6.867397	3.126274	0	16.22535
ln_emig_rate	17643	-4.373365	2.300796	-10.83623	3.010124
ln_wtemperature_origin	34694	2.841105	.5282457	-1.670807	3.387202
ln_wprecipitation_origin	35112	2.126556	.8059214	-2.721096	3.702957
ln_gdp_destination	35112	10.17991	.2379786	9.457096	10.85986
ln_gdp_origin	32205	8.061729	1.151494	4.810944	11.08494
ln_pop_origin	35112	15.34757	2.081953	9.754117	20.99407
Demographic pressure	33516	59.92756	6.530337	47.72374	81.71818
Unemployment origin	15542	10.10761	6.533774	.6	37.3
unemployment destination	35112	6.939474	3.316424	2	22.7
Trade_to_gdp	32642	85.44475	39.62456	.3088029	275.2324
ln_distance	35112	8.710436	.910424	1.334656	9.875896
Contiguity	35112	.0119617	.1087151	0	1
Same_continent	35112	.1555024	.3623881	0	1
Language	35112	.1032126	.3042407	0	1
Colony	35112	.0478469	.2134452	0	1
EU membership	35112	.2611073	.4392446	0	1



# Main Results

## Static Model

Dependent variable: <b>Ln_migration_flows</b>	LSDV with time and country dummies	LSDV with time and pair dummies	LSDV with host country-and-time and pair dummies
Independent variables:	M2	M3	M4
<b>Ln_wtemperature_origin</b>	0.098	0.182	<b>0.220*</b>
	(0.208)	(0.147)	(0.132)
<b>Ln_wprecipitation_origin</b>	-0.061**	-0.047*	<b>-0.049**</b>
	(0.030)	(0.025)	(0.022)
<b>Ln_GDP_destination</b>	1.840***	1.555***	
	(0.275)	(0.254)	
<b>Ln_GDP_origin</b>	1.453***	1.134***	1.105***
	(0.518)	(0.439)	(0.402)
<b>ln_GDP_origin_sq</b>	-0.095***	-0.082***	-0.078***
	(0.030)	(0.025)	(0.023)
<b>Demographic_preasure</b>	-0.002	0.015	0.020*
	(0.014)	(0.012)	(0.011)
<b>Unemployment_destination</b>	-0.086***	-0.123***	
	(0.011)	(0.010)	
<b>Trade_to_GDP ratio</b>	0.002**	0.002**	0.002***
	(0.001)	(0.001)	(0.001)
<b>Ln_distance</b>	-0.010		
	(0.034)		
<b>Contiguity</b>	-0.191		
	(0.214)		
<b>Same_continent</b>	1.528***		
	(0.132)		
<b>Common language</b>	0.982***		
	(0.124)		
<b>Colonial relationship</b>	2.134***		
	(0.173)		
<b>European Union Membership</b>	0.051	0.096***	0.041
	(0.044)	(0.032)	(0.057)
<b>R-squared</b>	0.772	0.203	0.316
<b>N</b>	16109	16109	16109

# Main Results Static Model (Cont)

<b>Dependent variable:</b> <b>Ln_migration_stock</b>	<b>LSDV with time dummies</b>	<b>LSDV with time and country dummies</b>	<b>LSDV with time and pair dummies</b>
<b>Independent variables:</b>	<b>M1</b>	<b>M2</b>	<b>M3</b>
<b>Ln_wtemperature_origin</b>	0.252*	0.761***	0.478***
	(0.143)	(0.268)	(0.180)
<b>Ln_wprecipitation_origin</b>	-0.166*	-0.035	-0.037
	(0.090)	(0.037)	(0.023)
<b>R-squared</b>	0.826	0.397	0.478
<b>N</b>	10785	10785	10785

<b>dep var:</b> <b>ln_migration_rates</b>	<b>LSDV with time and country dummies</b>	<b>LSDV with time and pair dummies</b>	<b>LSDV with host country-and-time and pair dummies</b>
<b>Independent variables:</b>	<b>M2</b>	<b>M3</b>	<b>M4</b>
<b>ln_wtemperature_origin</b>	0.147	0.227*	0.265**
<b>se</b>	(0.210)	(0.148)	(0.134)
<b>ln_wprecipitation_origin</b>	-0.064**	-0.051**	-0.052**
<b>se</b>	(0.030)	(0.024)	(0.022)
<b>R-squared</b>	0.723	0.164	0.280
<b>N</b>	16109	16109	16109

# Main Results Dynamic Model

dep var: ln_migration_flo ws	LSDV with time and country dummies	LSDV with time dummies and bilateral FE	Instrumental Variables First Diff.
Independent variables:	M2	M3	M4
ln_stocks (t-1)	0.171*** (0.013)	0.139*** (0.034)	0.039 (0.079)
ln_inflows (t-1)	0.739*** (0.015)	0.413*** (0.022)	-0.161** (0.070)
ln_wtem_origin se	0.171 (0.180)	0.126 (0.168)	-0.273 (0.201)
ln_wpre_origin se	-0.087*** (0.033)	-0.085*** (0.029)	-0.067*** (0.024)

Dep var: ln_emig_rates	ols, time dummies	time and i,j, fe	time and pair fe
Indep. Variables:	b/se	b/se	b/se
L.ln_emig_rate	0.927*** (0.006)	0.740*** (0.015)	0.409*** (0.023)
L.ln_stocks	0.026*** (0.005)	0.172*** (0.014)	0.147*** (0.034)
ln_wtem_or	-0.023* (0.013)	0.175 (0.181)	0.133 (0.169)
ln_wpre_or	-0.007 (0.007)	-0.090*** (0.033)	-0.085*** (0.030)

# Robustness I: Instrumental Variables

<b>Dep variables:</b>	<b>Instrumental Variables</b>
	<b>Ln_emig_rate</b>
<b>Indep. Var:</b>	b/se
<b>LD.ln_emig_rate</b>	-0.670*
	(0.362)
<b>LD.ln_stocks</b>	0.432
	(0.274)
<b>LD.ln_wtem_or</b>	-0.112
	(0.181)
<b>LD.ln_wpre_or</b>	-0.081***
	(0.029)

# Robustness II: Heckman

<b>Dependent variable:</b>	<b>Ln migration inflows</b>	<b>Migration inflows</b>
<b>Ln_wtemperature_origin</b>	0.313***	-0.035
se	-0.12	-0.037
<b>Ln_wprecipitation_origin</b>	-0.064**	-0.165***
se	-0.026	-0.027

<b>Stability (used as selection variable in the first step)</b>	Coeff	-0.395***
	se	-0.025